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**EXTENDED MULTIPLE MODELS SELECTION ALGORITHMS
BASED ON ITERATIVE FEASIBLE GENERALIZED LEAST
SQUARES (IFGLS) AND EXPECTATION-MAXIMIZATION (EM)
ALGORITHM**



**DOCTOR OF PHILOSOPHY
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of Arts And Sciences

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Abstrak

Pemilihan model automatik telah digunakan untuk merapatkan jurang antara pakar dan pengguna akhir sejak tahun 1960-an bermula dengan *Stepwise* dan baru-baru ini dengan *Autometrics* untuk satu persamaan. Pelanjutan *Autometrics* dalam pemilihan model ini juga dibangunkan untuk persamaan berganda dengan mengintegrasikannya dengan persamaan regresi seolah-olah tak terhubung (*SURE*) dan dianggarkan menggunakan penganggaran kuasa dua terkecil teritlak boleh-laksana (*FGLS*), yang dikenali sebagai algoritma *SURE-Autometrics*. Walau bagaimanapun, *SURE-Autometrics* tidak pernah dianggarkan menggunakan anggaran kebolehjadian maksimum (*MLE*). Oleh itu, dalam kajian ini, *SURE-Autometrics* ditambah baik menggunakan dua kaedah *MLE* iaitu kuasa dua terkecil teritlak boleh-laksana secara lelaran (*IFGLS*) dan algoritma pemaksimuman-jangkaan (*EM*), dikenali sebagai algoritma *SURE(IFGLS)-Autometrics* dan *SURE(EM)-Autometrics*. Kajian simulasi dan empirik dijalankan untuk mengesahkan prestasi dua algoritma tersebut. Dalam kajian simulasi, saiz sampel yang berbeza, kekuatan korelasi di antara persamaan, saiz model tanpa batas umum (*GUMS*), bilangan persamaan, paras keertian dan model spesifikasi benar digunakan untuk menilai peratusan dalam mencari *GUMS* yang sebenar. Manakala, dalam kajian empirik, dua set data empirik iaitu kadar pertumbuhan negara dan indeks kualiti air (*WQI*) dinilai menggunakan punca min ralat kuasa dua dan punca min ralat kuasa dua geometri, di mana 18 prosedur pemilihan model secara manual dan automatik dibandingkan. Keputusan simulasi menunjukkan bahawa prestasi algoritma *SURE(IFGLS)-Autometrics* dan *SURE(EM)-Autometrics* bertambah baik dalam keadaan sampel yang besar, korelasi yang kuat antara persamaan, *GUMS* kecil, bilangan persamaan yang kecil, paras keertian yang ketat dan di dalam model kosong (tanpa pembolehubah peramal). Keputusan empirik bagi kedua-dua algoritma berprestasi baik berbanding prosedur pemilihan model yang lain, terutamanya menggunakan data *WQI* di mana saiz sampel lebih besar dan mempunyai data yang berkualiti. Kesimpulannya, *SURE(IFGLS)-Autometrics* dan *SURE(EM)-Autometrics* boleh digunakan sebagai algoritma pemilihan model. Sebagai tambahan, kedua-dua algoritma adalah sesuai untuk meningkatkan prestasi prosedur pemilihan model automatik. Penemuan umum menyokong idea bahawa prosedur automatik mengatasi prosedur manual.

Kata kunci: Pemilihan model, persamaan regresi seolah-olah tak terhubung, anggaran kebolehjadian maksimum, kuasa dua terkecil teritlak boleh-laksana secara lelaran, algoritma pemaksimuman-jangkaan.

Abstract

Automated model selection has been used to bridge the gap between experts and end users since 1960s starting with *Stepwise* and recently with *Autometrics* for single equation. This extension of *Autometrics* for model selection was also developed for multiple equations by integrating it with seemingly unrelated regressions equations (SURE) and estimated using feasible generalized least squares (FGLS), known as *SURE-Autometrics* algorithm. However, *SURE-Autometrics* has not been estimated using maximum likelihood estimation (MLE). Therefore, in this study *SURE-Autometrics* is improvised using two MLE methods, which are iterative feasible generalized least squares (IFGLS) and expectation-maximization (EM) algorithm, named as *SURE(IFGLS)-Autometrics* and *SURE(EM)-Autometrics* algorithms. Simulation and empirical studies are conducted in validating the performance of the two algorithms. In the simulation study, different sample sizes, strength of correlation among equations, size of general unrestricted model (GUMS), number of equations, significance levels and true specification models are incorporated by evaluating the percentages of finding the true GUMS. While in the empirical study, two empirical data sets which are national growth rates and water quality index (WQI) are assessed using root mean square error and geometric root mean square error where 18 models selection procedures of manual and automated approaches are compared. The simulation results indicated that performance of *SURE(IFGLS)-Autometrics* and *SURE(EM)-Autometrics* algorithms improved in conditions of large sample, strong correlation among equations, small GUMS, a smaller number of equations, tight significance level and in an empty model (without predictor variables). The empirical results for both algorithms performed well as compared to other models selection procedures, particularly using WQI data where the sample size is bigger and has good quality data. In conclusion, *SURE(IFGLS)-Autometrics* and *SURE(EM)-Autometrics* can be used as models selection algorithms. Additionally, both algorithms are suitable in improving performance of automated models selection procedures. General findings support the idea that automated procedures surpass the manual procedures.

Keywords: Models selection, seemingly unrelated regression equations, maximum likelihood estimation, iterative feasible generalised least squares, expectation-maximization algorithm.

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List of Abbreviations

ARCH	autoregressive conditional heteroscedasticity
DGP	data-generating process
e.g.	for example
EM	expectation-maximization
et al.	and others
etc	and so forth
FGLS	feasible generalised least squares
FIML	full information maximum likelihood
IFGLS	iterative feasible generalised least squares
GDP	gross domestic product
GETS	general-to-specific
GLS	general least squares
GRMSE	geometric root mean square error
GUM	general unrestricted model for single equation
GUMS	general unrestricted model for multiple equations
i.e.	that is
i.i.d	independent and identical
LM	Lagrange multiplier
LR	likelihood ratio
ML	maximum likelihood
MLE	maximum likelihood estimation
MC-QLR	Monte Carlo quasi-likelihood ratio
MI	multivariate independent
OLS	ordinary least squares
RMSE	root mean square error
SUM	specific unrestricted model
SURE	seemingly unrelated regression equations
SURR	seemingly unrelated restricted residuals
SUUR	seemingly unrelated unrestricted residuals
WQI	water quality index

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

A model is generally used as an instrument in understanding a concept or phenomenon of the real world. In other words, a model plays a vital role in assessing interactions among variables involved and in forecasting the effect of changes in some variables towards the future course of others. A good model is therefore needed to test the necessary hypothesis and forecast accurately which lead to good decision making for the future either for planning or controlling (Hendry & Pretis, 2016).

Some criteria have been identified in judging a good model which includes the parsimony of the model. This is important as a model is functioned to capture the essence of an event. Hence, a simpler model is more favoured compared to unreasonably large one when other things are equal (Zucchini, 2000). Apart from being parsimonious, goodness of fit with a high adjusted R-square where the sample data fitted to the model relatively well is also advantageous in a statistical modelling.

Any models should be consistent with the theory related. Significant variables are supposedly retained, while the irrelevant ones are to be excluded. The coefficients in model are expected to have right signs, especially when the model is used for forecasting. This predictive power of the model, which is referred to the capability of a model to produce testable predictions, is also taken into account (Harrell, 2015). One way to examine this is through comparison of the model's forecast with experience. Practically, these criteria need to be considered critically in order to select

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APPENDIX A

AUTOMETRICS ALGORITHM

0.0 Estimate the initial GUM.

This initializes the search procedure.

0.1 (optional) Lag-length pre-search.

0.2 Test all regressors at a loose significance level.

If passed, accept the empty model as the final model, provided diagnostic testing is satisfied, then stop.

1.0 Set $i = 0$.

The starting point for the current iteration is GUM 0 (this may be the same as the initial GUM), which has k free regressors.

1.1 (Convergence) If all regressors in the GUM are significant then stop.

This is at a slightly more stringent p -value to allow for ‘squeezing’.

1.2 Update the diagnostic p -values.

Ideally, the user ensures that the initial GUM passes the diagnostic tests. However, when this is not the case, the p -value for each failed test statistic is increased. Subsequently, the p -values are adjusted downwards again if possible.

1.3 Run reduction over the root branches.

Terminal candidate models (‘terminals’) are collected as the search progresses. Any subtree that has a previously found terminal nested in it is skipped to speed up the search. This will result in one or more terminal.

1.4 Run reduction to search for nested terminals.

Revisit the subtrees that were skipped before. At each point it is possible to compute the minimal contrast with a known terminal to jump ahead to a possible new (non-nested) terminal. If the union of terminals after the previous step 1.3 is smaller than the union from the previous iteration, then use union contrast, otherwise use terminal contrast.

1.5 Remove terminals that fail diagnostics.

If the p -values, p_d for diagnostic testing had to be adjusted downwards, and there are some terminals that pass the original p -values, then keep only those terminal models which pass and reset p_d to the original value.

1.6 Form the union of the terminal models.

The union is called the *current* GUM or GUM $i + 1$.

1.7 Remove terminals that fail backtesting.

When using the default Autometrics settings, this step is skipped, because backtesting with respect to GUM 0 has already been done as an integral part of the tree search: there are no terminals that fail.

Optionally, the PcGets default backtesting with respect to the current GUM can be adopted instead. In that case, there may be terminals that fail the encompassing test against the new GUM.

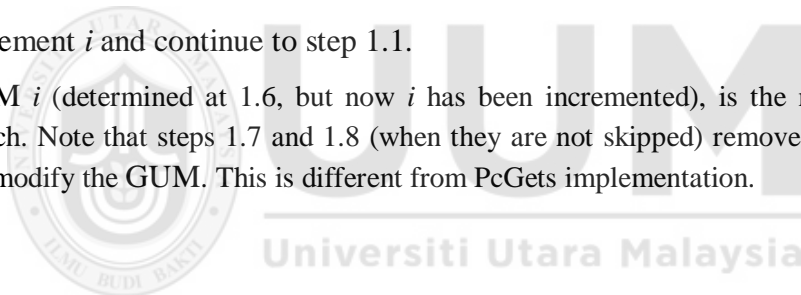
1.8 Remove terminals with insignificant variables.

When using the default Autometrics settings, this step is skipped because a terminal remains a terminal candidate for subsequent iterations.

However, this step is relevant when the PcGets default is used in 1.7: backtesting is with respect to the current GUM, which changes between iterations. So a terminal candidate with insignificant variables may not be a terminal next time.

1.9 Increment i and continue to step 1.1.

GUM i (determined at 1.6, but now i has been incremented), is the new base for the search. Note that steps 1.7 and 1.8 (when they are not skipped) remove terminals but do not modify the GUM. This is different from PcGets implementation.



APPENDIX B

SURE(IFGLS)-AUTOMETRICS OR SURE(EM)-AUTOMETRICS

ALGORITHM

Phase 1: Estimation of Initial General Unrestricted Model (GUMS)

Step 0

Declare number of equations, including regressands and regressors for each equation.

Create lag variables.

Set main level of significance, p_a .

Step 1

Run diagnostic analyses of each equation using OLS estimation at diagnostic p -value, p_d .

- If all tests are satisfied, continue next step.
- Otherwise, update the p_d , then continue next step.

Step 2

Test the contemporaneous correlation of disturbances amongst the equations.

- If significant (p -value < 0.10), it indicates that IFGLS or EM algorithm estimation is more efficient than OLS.
- Otherwise, proceed with model estimation using OLS method, and then stop.

Step 3

Estimate the multiple equations model using IFGLS or EM algorithm method.

- If all regressors are significant, the equations become the final GUMS, and then stop.
- Otherwise, the equations become the initial GUMS, and then proceed to next phase.

Phase 2: Pre-search Lag Reduction

Step 0

Set pre-search p -value, p_p .

Step 1

Run closed lag, then common lag, and followed by common- X lag reductions to obtain a reduced model.

Step 2

Run common- X lag, then common lag, and followed by closed lag reductions to obtain another reduced model.

Step 3

Run encompassing tests of reduced models in Step 1 and Step 2 against the union of these models at p_a .

- If only one model passed the test, the model is the current GUMS.
- Otherwise, the union become the current GUMS, and then stop.

Step 4

Repeat Step 1 and 2 in Phase 1 for the current GUMS.

Phase 3: Tree Search over Root Branches

Step 0

Remove all regressors and test at p_a .

- If passed, accept the empty model. Repeat Step 1 and 2 in Phase 1.
 - If satisfied, the empty model is the final GUMS, then stop.
 - Otherwise, continue next step.
- Otherwise, continue next step.

Step 1

Set p -value for bunching, p_b and p -value for chopping, p_c .

Set $i = 0$. Denote current GUMS as GUMS 0.

Step 2

Check all regressors in GUMS 0.

- If all regressors are significant, accept as the final GUMS, and then stop.
- Otherwise, continue next step.

Step 3

Run root branches reduction using IFGLS or EM algorithm estimation.

- Implement pruning, bunching and chopping principles as the search progress.
- Any models that cannot be reduced any further are known as terminal candidate models.
- Collect all terminals as the search progresses.
- Any sub-tree that has a previously found terminal nested in it is skipped.

Phase 4: Tree Search for Nested Terminals

Step 0

Revisit the sub-trees that were skipped before.

Form terminal contrasts by using the minimal contrasts from the existence terminals.

Step 1

Union the terminals

- If the union is smaller than the GUM i , then use union contrast.
- Otherwise, use terminal contrast.

Step 2

Remove terminals.

- Terminals that fail diagnostic tests.
- Terminals with insignificant variables.

Step 3

New base for the search.

- If union contrast used, form the union of the terminals. The union is called the current GUMS or GUMS $i + 1$. Go to Step 1 in Phase 3 for iteration.
- Otherwise, continue to Phase 5.

Phase 5: Selection of Final Model

Step 0

Calculate information criteria for each equation in all terminal models. Then, find average values for each terminal model.

Step 1

Select final model based on smallest average value of Schwartz criterion. The model is known as specific unrestricted model.

Step 2

Estimate the specific unrestricted model using IFGLS or EM estimation.

Step 3

Run diagnostic analyses of each equation and test the contemporaneous correlation of disturbances amongst the equations

APPENDIX C

ESTIMATED MODELS OF NATIONAL GROWTH RATES

Country	Estimation Method	Constant	Δy_{it-1}	Δy_{it-2}	Δx_{it}	$\Delta x_{it(t-1)}$
Denmark	OLS	-0.008 (-0.816)	-0.225 (-1.465)	0.124 (-1.244)	-0.042 (-0.726)	0.050 (-0.804)
	FGLS	-0.009 (-1.015)	-0.312** (-2.649)	0.168** (-2.096)	-0.009 (-0.192)	0.068 (-1.424)
	IFGLS	-0.010 (-1.087)	-0.357*** (-3.573)	0.196** (-2.664)	0.008 (-0.211)	0.102** (-2.470)
	EM	-0.010 (-0.989)	-0.356** (-2.631)	0.195** (-2.085)	0.008 (-0.334)	0.101 (-1.435)
Ireland	OLS	0.009 (-1.208)	0.265 (-1.577)	-0.031 (-0.381)	0.021 (0.360)	0.029 (-0.488)
	FGLS	0.008 (-1.278)	0.305** (-2.253)	-0.009 (-0.141)	-0.021 (-0.451)	0.051 (-1.047)
	IFGLS	0.007 (-1.020)	0.295** (-2.508)	0.051 (-0.875)	-0.050 (-1.235)	0.066 (-1.588)
	EM	0.007 (-1.247)	0.296** (-2.190)	0.050 (-0.164)	-0.050 (-0.436)	0.066 (-1.066)
Netherlands	OLS	0.013 (-1.115)	0.016 (-0.088)	-0.007 (-0.074)	0.191 (-1.654)	0.039 (-0.319)
	FGLS	0.016 (-1.542)	-0.090 (-0.593)	-0.001 (-0.007)	0.190* (-1.954)	0.100 (-0.964)
	IFGLS	0.018 (-1.674)	-0.165 (-1.126)	0.010 (-0.127)	0.193** (-2.058)	0.128 (-1.282)
	EM	0.018 (-1.493)	-0.164 (-0.579)	0.010 (-0.023)	0.193* (-1.913)	0.129 (-0.943)
United Kingdom	OLS	0.001 (-0.131)	-0.008 (-0.050)	-0.059 (-0.558)	-0.044 (-0.193)	0.064 (-0.300)
	FGLS	0.001 (-0.106)	-0.067 (-0.479)	-0.099 (-1.097)	-0.035 (-0.181)	-0.067 (-0.374)
	IFGLS	0.001 (-0.051)	-0.140 (-1.119)	-0.162* (-1.947)	-0.017 (-0.100)	-0.263* (-1.729)
	EM	0.001 (-0.054)	-0.138 (-0.350)	-0.160 (-1.137)	-0.018 (-0.226)	-0.259 (-0.135)

***Significant at 1%, ** Significant at 5%, * Significant at 10%, () *t*-value

(cont.)

Country	Estimation Method	Δx_{i2t}	$\Delta x_{i2(t-1)}$	Δx_{i3t}	$\Delta x_{i3(t-1)}$	\overline{R}^2	Standard errors
Denmark	OLS	-0.069 (-0.561)	0.188 (-1.474)	0.811*** (-8.704)	0.309 (-2.066)	0.721	0.058
	FGLS	-0.113 (-1.097)	0.182* (-1.709)	0.790*** (-10.780)	0.339*** (-3.010)	0.712	0.053
	IFGLS	-0.110 (-1.070)	0.143 (-1.338)	0.730*** (-11.315)	0.397*** (-4.274)	0.693	0.054
	EM	-0.111 (-0.887)	0.144 (-1.630)	0.732*** (-10.664)	0.395*** (-2.916)	0.694	0.054
Ireland	OLS	-0.109 (-1.014)	0.037 (-0.340)	0.707*** (-9.585)	-0.142 (-1.008)	0.791	0.042
	FGLS	-0.045 (-0.498)	0.004 (-0.043)	0.696*** (-11.516)	-0.158 (-0.112)	0.786	0.038
	IFGLS	-0.006 (-0.064)	-0.034 (-0.387)	0.732*** (-13.582)	-0.155 (-1.609)	0.772	0.039
	EM	-0.006 (-0.534)	-0.033 (-0.028)	0.730*** (-11.388)	-0.156 (-1.373)	0.772	0.039
Netherlands	OLS	-0.322 (-1.683)	-0.058 (-0.272)	0.909*** (-9.378)	-0.010 (-0.057)	0.740	0.054
	FGLS	-0.352** (-2.145)	-0.122 (-0.671)	0.844*** (-10.082)	0.099 (-0.639)	0.724	0.049
	IFGLS	-0.374** (-2.307)	-0.143 (-0.797)	0.797*** (-9.644)	0.173 (-1.157)	0.692	0.052
	EM	-0.374** (-2.077)	-0.144 (-0.675)	0.797*** (-9.977)	0.172 (-0.630)	0.693	0.052
United Kingdom	OLS	-0.134 (-0.94)	0.103 (-0.527)	0.472*** (-7.260)	-0.074 (-0.732)	0.619	0.068
	FGLS	-0.109 (-0.649)	0.161 (-0.955)	0.474*** (-8.538)	-0.018 (-0.210)	0.612	0.061
	IFGLS	-0.070 (-0.438)	0.257 (-1.626)	0.466*** (-9.527)	0.064 (-0.885)	0.576	0.064
	EM	-0.071 (-0.780)	0.255 (-0.617)	0.466*** (-8.507)	0.062 (-0.392)	0.577	0.063

***Significant at 1%, ** Significant at 5%, * Significant at 10%, () *t*-value

APPENDIX D

ESTIMATED MODELS OF WQI

Variables	S6				S7			
	OLS	FGLS	IFGLS	EM	OLS	FGLS	IFGLS	EM
Constant	67.206*** (4.502)	64.899*** (5.199)	63.728*** (5.220)	66.314*** (5.226)	51.275*** (3.715)	61.649*** (5.514)	73.161*** (6.763)	60.826*** (6.757)
Δy_{it-1}	-0.083 (-0.685)	-0.025 (-0.244)	-0.018 (-0.189)	-0.046 (-0.191)	-0.282** (2.143)	0.143 (1.397)	0.070 (0.770)	0.127 (0.775)
Δy_{it-2}	-0.010 (-0.288)	-0.018 (-0.635)	-0.016 (-0.598)	-0.023 (-0.599)	-0.026 (-0.797)	-0.030 (-1.173)	-0.036 (-1.549)	-0.034 (-1.549)
Δy_{it-3}	-0.064 (1.752)	0.036 (1.181)	0.013 (0.441)	0.048 (0.450)	-0.033 (-0.912)	-0.017 (-0.598)	0.002 (0.082)	-0.014 (0.072)
Δx_{i1t}	0.092 (0.321)	0.223 (0.935)	0.452* (1.940)	0.141 (1.930)	0.096 (0.698)	0.157 (1.463)	0.172* (1.816)	0.140 (1.812)
$\Delta x_{i1(t-1)}$	-0.318 (-1.037)	-0.257 (-1.010)	-0.175 (-0.692)	-0.218 (-0.694)	0.097 (0.699)	0.099 (0.907)	0.125 (1.284)	0.085 (1.281)
Δx_{i2t}	1.689 (0.460)	-0.097 (-0.032)	-3.071 (-1.035)	0.982 (-1.024)	1.533 (0.915)	0.978 (0.748)	0.952 (0.822)	1.086 (0.821)
$\Delta x_{i2(t-1)}$	4.228 (1.069)	3.168 (0.966)	1.906 (0.587)	2.637 (0.590)	-2.061 (-1.228)	-1.761 (-1.341)	-1.977* (-1.699)	-1.585 (-1.696)
Δx_{i3t}	-0.563*** (-4.806)	-0.589*** (-6.084)	-0.618*** (-6.625)	-0.579*** (-6.619)	-0.597*** (-4.731)	-0.601*** (-5.916)	-0.631*** (-6.694)	-0.589*** (-6.686)
$\Delta x_{i3(t-1)}$	-0.103 (-0.785)	-0.117 (-1.087)	-0.149 (-1.423)	-0.130 (-1.421)	0.109 (0.778)	0.003 (0.034)	-0.057 (-0.554)	0.001 (-0.547)
Δx_{i4t}	-0.186*** (-4.245)	-0.176*** (-4.848)	-0.169*** (-4.823)	-0.171*** (-4.824)	-0.205*** (-4.472)	-0.191*** (-5.213)	-0.170*** (-5.055)	-0.192*** (-5.062)
$\Delta x_{i4(t-1)}$	0.004 (0.086)	0.018 (0.431)	0.029 (0.736)	0.019 (0.730)	0.042 (0.879)	0.024 (0.633)	0.019 (0.542)	0.019 (0.540)
Δx_{i5t}	-0.137*** (-0.095)	-0.054*** (-16.510)	-0.053*** (-16.821)	-0.054*** (-16.824)	-0.076*** (-12.249)	-0.076*** (-15.466)	-0.080*** (-18.308)	-0.076*** (-18.286)
$\Delta x_{i5(t-1)}$	-0.003 (-0.385)	-0.000 (-0.065)	-0.002 (-0.346)	-0.002 (-0.344)	0.032*** (2.758)	0.019** (2.029)	0.011 (1.342)	0.018 (1.347)
Δx_{i6t}	-0.137 (-0.095)	0.037 (0.031)	0.186 (0.158)	0.261 (0.154)	-0.150 (-0.116)	-0.488 (-0.471)	-0.962 (-0.977)	-0.137 (-0.974)
$\Delta x_{i6(t-1)}$	0.038 (0.028)	0.254 (0.223)	0.707 (0.635)	-0.023 (0.629)	0.481 (0.361)	0.507 (0.471)	0.002 (0.002)	0.535 (0.009)
Δx_{i7t}	-0.710*** (-5.001)	-0.868*** (-7.302)	-1.040*** (-9.008)	-0.883*** (-8.999)	-1.293*** (-8.322)	-1.374*** (-11.167)	-1.522*** (-13.788)	-1.392*** (-13.777)
$\Delta x_{i7(t-1)}$	-0.074 (-0.422)	-0.071 (-0.484)	-0.116 (-0.788)	-0.105 (-0.788)	0.460** (2.105)	0.261 (1.498)	0.113 (0.695)	0.237 (0.700)
\overline{R}^2	0.942	0.939	0.931	0.933	0.946	0.942	0.930	0.933
Std. errors	2.330	2.091	2.238	2.236	1.575	1.423	1.563	1.562

***Significant at 1%, ** Significant at 5%, * Significant at 10%, () *t*-value

(cont.)

Variables	S8				S25			
	OLS	FGLS	IFGLS	EM	OLS	FGLS	IFGLS	EM
Constant	41.967*** (3.039)	45.299*** (3.966)	52.039** * (5.076)	45.117** * (5.071)	49.318** * (3.224)	58.906** * (4.709)	65.651** * (5.589)	58.515** * (5.593)
Δy_{it-1}	0.165 (1.237)	0.144 (1.340)	0.114 (1.266)	0.141 (1.266)	0.213* (1.681)	0.178* (1.753)	0.160* (1.727)	0.171* (1.726)
Δy_{it-2}	0.046 (1.273)	0.058** (2.027)	0.062** (2.649)	0.058** (2.655)	-0.023 (-0.667)	-0.039 (-1.440)	-0.047* (-1.866)	-0.041 (-1.870)
Δy_{it-3}	-0.022 (-0.700)	-0.037 (-1.448)	-0.049** (-2.383)	-0.035 (-2.372)	0.058* (1.875)	0.050** (2.002)	0.049** (2.150)	0.050** (2.152)
Δx_{i1t}	0.132 (0.674)	0.161 (1.015)	0.233** (1.775)	0.140 (1.760)	-0.020 (-0.090)	0.050 (0.278)	0.079 (0.476)	0.020 (0.478)
$\Delta x_{i1(t-1)}$	0.140 (0.716)	0.171 (1.085)	0.200 (1.543)	0.181 (1.549)	-0.181 (-0.939)	-0.082 (-0.528)	-0.002 (-0.016)	-0.077 (-0.016)
Δx_{i2t}	2.178 (0.871)	1.828 (0.902)	0.932 (0.553)	2.072 (0.567)	3.013 (1.057)	2.189 (0.957)	1.874 (0.894)	2.544 (0.892)
$\Delta x_{i2(t-1)}$	-2.624 (-1.058)	-2.950 (-1.475)	-3.256* (-1.984)	-3.081 (-1.990)	1.659 (0.668)	0.508 (0.253)	-0.445 (-0.240)	0.406 (-0.240)
Δx_{i3t}	-0.675*** (-5.397)	-0.632*** (-6.146)	-0.594*** (-6.641)	-0.636*** (-6.641)	-0.741*** (-4.240)	-0.671*** (-4.685)	-0.643*** (-4.804)	-0.656*** (-4.805)
$\Delta x_{i3(t-1)}$	0.019 (0.128)	-0.083 (-0.674)	-0.196* (-1.854)	-0.076 (-1.841)	0.576*** (2.709)	0.480*** (2.765)	0.400** (2.471)	0.473*** (2.474)
Δx_{i4t}	-0.121*** (-2.716)	-0.138*** (-3.779)	-0.149*** (-4.830)	-0.134*** (-4.824)	-0.144** (-2.370)	-0.152*** (-3.080)	-0.156*** (-3.393)	-0.152*** (-3.385)
$\Delta x_{i4(t-1)}$	0.020 (0.460)	0.049 (1.363)	0.074** (2.391)	0.046 (2.382)	-0.108* (-1.723)	-0.106** (-2.067)	-0.087* (-1.803)	-0.106** (-1.811)
Δx_{i5t}	-0.061*** (-7.312)	-0.060*** (-8.895)	-0.058*** (-10.584)	-0.060*** (-10.577)	-0.076*** (-8.370)	-0.075*** (-10.196)	-0.076*** (-11.059)	-0.073*** (-11.066)
$\Delta x_{i5(t-1)}$	0.016 (1.546)	0.010 (1.199)	0.003 (0.527)	0.010 (0.533)	0.013 (0.845)	0.007 (0.537)	0.003 (0.283)	0.006 (0.280)
Δx_{i6t}	-0.312 (-0.224)	-0.408 (-0.355)	-0.657 (-0.649)	-0.236 (-0.647)	0.646 (0.488)	0.001 (0.001)	-0.322 (-0.320)	0.241 (-0.330)
$\Delta x_{i6(t-1)}$	1.485 (1.067)	1.417 (1.236)	1.243 (1.215)	1.319 (1.213)	-0.210 (-0.158)	-0.300 (-0.275)	-0.658 (-0.641)	-0.356 (0.637)
Δx_{i7t}	-1.239*** (-7.926)	-1.375*** (-10.863)	-1.565*** (-14.710)	-1.368*** (-14.693)	-1.498*** (-8.579)	-1.694*** (-11.917)	-1.826*** (-13.846)	-1.718*** (-13.858)
$\Delta x_{i7(t-1)}$	0.496** (2.275)	0.409** (2.275)	0.291* (1.804)	0.395 (1.803)	0.328 (1.262)	0.326 (1.534)	0.300 (1.507)	0.299 (1.505)
\overline{R}^2	0.949	0.946	0.937	0.939	0.944	0.942	0.938	0.939
Std. errors	1.684	1.508	1.630	1.629	2.027	1.817	1.878	1.879

***Significant at 1%, ** Significant at 5%, * Significant at 10%, () *t*-value

APPENDIX E

DATA OF NATIONAL GROWTH RATES

1. Denmark

Year	GDP	Money (M1)	Stock	Year	GDP	Money (M1)	Stock
1951	23.10	6.17	7.00				
1952	24.70	6.57	6.00	1978	311.40	65.06	27.00
1953	26.40	7.07	6.00	1979	346.90	71.88	26.00
1954	27.70	6.93	7.00	1980	373.80	77.51	24.00
1955	28.90	7.10	8.00	1981	407.80	88.03	40.00
1956	30.90	7.43	8.00	1982	464.50	91.66	51.00
1957	32.90	7.79	9.00	1983	512.50	113.30	89.00
1958	34.30	8.85	9.00	1984	565.30	128.08	96.00
1959	38.10	9.82	11.00	1985	615.10	156.49	100.00
1960	40.80	10.03	12.00	1986	666.50	167.97	101.00
1961	45.60	11.14	12.00	1987	699.90	188.45	84.00
1962	51.40	12.21	12.00	1988	732.10	225.11	95.00
1963	54.30	13.86	12.00	1989	769.80	226.11	132.00
1964	62.00	15.23	14.00	1990	800.00	244.48	146.00
1965	69.70	16.97	14.00	1991	857.65	258.27	157.00
1966	77.20	19.34	15.00	1992	887.87	256.00	144.37
1967	84.80	21.12	12.00	1993	900.15	283.00	147.30
1968	94.40	24.06	12.00	1994	965.72	279.05	175.81
1969	107.30	27.13	14.00	1995	1009.76	291.98	175.49
1970	118.60	27.47	13.00	1996	1060.89	325.52	214.70
1971	131.10	29.61	12.00	1997	1116.32	344.05	283.44
1972	150.70	33.64	17.00	1998	1155.41	360.74	306.47
1973	172.90	37.59	26.00	1999	1207.75	381.77	272.37
1974	193.60	39.36	19.00	2000	1278.96	385.98	438.70
1975	216.30	49.86	21.00	2001	1325.51	414.85	447.36
1976	251.20	52.34	28.00	2002	1360.71	430.82	447.91
1977	279.30	56.08	29.00	2003	1395.85	469.15	448.75

2. Ireland

Year	GDP	Money (M1)	Stock	Year	GDP	Money (M1)	Stock
1951	392.00	132.00	9.90				
1952	450.00	137.00	8.30	1978	6757.00	1367.00	64.30
1953	496.00	145.00	7.40	1979	7917.00	1479.00	68.80
1954	498.00	152.00	8.10	1980	9361.00	1686.00	67.00
1955	522.00	155.00	8.50	1981	11359.00	1743.00	69.60
1956	530.00	155.00	7.70	1982	13382.00	1838.00	56.80
1957	549.00	166.00	7.00	1983	14779.00	2048.00	70.60
1958	568.00	165.00	7.00	1984	16407.00	2245.00	93.70
1959	608.00	171.00	9.30	1985	17790.00	2288.00	100.00
1960	631.00	203.00	11.70	1986	18877.00	2382.00	157.00
1961	680.00	219.00	13.90	1987	20263.00	2640.00	226.70
1962	736.00	241.00	15.90	1988	21815.00	2826.00	222.50
1963	791.00	278.00	19.40	1989	24307.00	3112.00	396.90
1964	901.00	287.00	24.10	1990	25693.00	3346.00	486.30
1965	959.00	298.00	23.40	1991	29675.00	3390.00	447.30
1966	1010.00	315.00	21.90	1992	31529.00	3451.00	416.01
1967	1104.00	341.00	21.80	1993	34054.00	3789.00	519.67
1968	1245.00	364.00	31.10	1994	36624.00	4124.00	593.00
1969	1438.00	389.00	32.90	1995	41409.00	4369.00	648.71
1970	1621.00	415.00	28.90	1996	45634.00	4897.00	811.40
1971	1853.00	440.00	28.10	1997	52760.00	5230.00	1101.21
1972	2238.00	518.00	41.30	1998	60582.00	5466.00	1548.57
1973	2729.00	572.00	48.80	1999	70576.80	5763.00	1594.95
1974	2991.00	624.00	32.80	2000	80997.00	5842.00	1704.36
1975	3792.00	748.00	32.40	2001	90367.50	6237.00	1844.07
1976	4653.00	875.00	33.80	2002	101867.00	6690.00	1486.74
1977	5703.00	1072.00	42.40	2003	103897.00	7068.00	1396.09

3. Netherlands

Year	GDP	Money (M1)	Stock	Year	GDP	Money (M1)	Stock
1951	21.40	7.04	13.20				
1952	22.40	7.76	11.90	1978	297.00	60.19	45.60
1953	23.80	8.26	13.10	1979	316.00	61.87	41.20
1954	26.60	8.85	16.30	1980	336.80	65.58	35.30
1955	29.70	9.58	20.50	1981	352.80	64.03	37.40
1956	32.00	9.23	21.40	1982	368.90	72.30	39.20
1957	34.70	9.05	18.90	1983	381.10	79.66	59.20
1958	35.10	10.13	19.30	1984	400.20	85.00	73.00
1959	37.40	10.59	28.00	1985	418.20	90.77	100.00
1960	41.80	11.30	38.80	1986	428.60	97.21	149.00
1961	44.20	12.16	49.40	1987	430.20	103.71	132.60
1962	47.60	13.09	44.50	1988	449.40	111.31	117.90
1963	51.60	14.29	44.90	1989	474.40	119.02	155.10
1964	60.70	15.44	44.90	1990	504.20	124.29	110.80
1965	67.80	16.99	44.00	1991	520.72	129.72	127.80
1966	73.80	18.16	37.30	1992	555.17	137.67	133.96
1967	81.00	19.29	41.80	1993	577.43	148.16	155.38
1968	89.80	21.49	48.90	1994	590.25	148.46	184.00
1969	101.70	23.23	53.90	1995	601.93	155.01	198.92
1970	121.20	25.95	55.00	1996	605.79	164.06	267.30
1971	136.50	29.85	52.10	1997	646.40	176.25	388.53
1972	154.30	35.12	62.60	1998	666.00	180.40	520.27
1973	176.00	35.14	69.10	1999	686.30	192.62	566.04
1974	199.80	39.43	53.40	2000	712.60	214.48	667.29
1975	220.00	47.20	53.10	2001	734.60	223.74	511.17
1976	251.90	51.05	50.70	2002	773.33	244.62	365.50
1977	274.90	57.77	45.80	2003	800.10	277.73	421.65

4. United Kingdom

Year	GDP	Money (M1)	Stock	Year	GDP	Money (M1)	Stock
1951	14.57	5.65	7.80				
1952	15.81	5.67	7.90	1978	169.62	27.36	34.00
1953	17.05	5.85	7.80	1979	198.46	29.86	38.60
1954	17.98	6.08	7.80	1980	232.55	31.04	41.30
1955	19.35	6.01	8.00	1981	256.37	34.59	46.60
1956	20.91	6.04	8.30	1982	279.58	40.66	53.90
1957	22.11	5.94	8.60	1983	305.42	42.46	68.10
1958	23.05	6.09	8.60	1984	324.63	48.05	81.00
1959	24.29	6.60	11.70	1985	355.94	56.67	100.00
1960	25.74	6.63	14.10	1986	383.14	69.27	124.10
1961	27.48	6.76	14.60	1987	420.86	154.12	163.80
1962	28.80	6.40	13.50	1988	467.23	170.67	147.40
1963	30.65	7.32	15.40	1989	511.50	195.31	176.50
1964	33.42	7.56	16.40	1990	549.51	214.94	173.30
1965	35.90	7.85	15.40	1991	575.36	229.23	190.20
1966	38.30	7.84	15.50	1992	610.85	253.99	198.67
1967	40.52	8.44	16.60	1993	642.33	318.89	228.03
1968	43.99	8.78	23.50	1994	681.33	337.98	245.13
1969	47.01	8.81	23.20	1995	719.18	402.63	255.12
1970	51.68	9.64	20.50	1996	763.29	447.40	289.08
1971	58.08	11.09	24.20	1997	810.94	485.86	327.21
1972	64.35	12.66	30.90	1998	859.44	510.34	383.95
1973	74.36	13.30	26.70	1999	903.87	552.38	391.42
1974	84.68	14.74	15.70	2000	951.27	613.80	415.86
1975	106.98	17.48	19.60	2001	994.04	666.57	428.78
1976	127.78	19.47	23.50	2002	1043.31	700.15	457.17
1977	147.12	23.52	30.20	2003	1099.36	757.83	475.31

APPENDIX F DATA OF WQI

1. Station S6

WEEK	WQI	DO (%)	DO (mg/L)	BOD	COD	SS	pH	NH3N
11-05-2012	69.45	73.7	5.71	7	22	45	7.26	2.78
15-05-2012	41.19	23.4	1.83	12	36	243	7.18	1.80
21-05-2012	68.05	51.7	4.07	12	32	40	7.21	0.17
31-05-2012	55.15	35.1	2.74	9	36	69	7.03	1.62
08-06-2012	37.39	10.3	0.80	19	58	46	6.87	8.33
15-06-2012	60.94	10.3	0.81	6	27	36	6.94	0.28
20-06-2012	44.98	32.6	2.51	18	42	41	7.09	9.87
27-06-2012	48.65	33.7	2.67	14	42	23	7.06	9.73
03-07-2012	57.79	58.2	4.53	8	31	88	7.10	5.71
10-07-2012	62.16	77.2	5.76	12	32	52	6.49	4.81
17-07-2012	51.61	24.7	1.97	8	27	33	6.87	7.60
24-07-2012	53.68	15.8	1.23	4	15	45	6.85	7.46
03-08-2012	55.74	34.0	2.70	8	24	20	6.88	6.51
10-08-2012	55.96	33.4	2.60	8	25	13	7.07	8.36
16-08-2012	57.78	53.5	4.31	5	16	186	7.00	2.47
23-08-2012	67.77	56.2	4.47	3	9	39	6.89	4.09
04-09-2012	42.88	54.5	4.26	19	46	156	7.04	8.91
11-09-2012	58.74	55.1	4.41	8	23	83	7.43	3.64
18-09-2012	66.45	42.6	3.34	5	14	60	7.46	0.92
25-09-2012	57.69	49.8	3.88	10	28	31	7.17	4.69
02-10-2012	46.36	48.4	3.83	10	33	202	7.08	5.04
09-10-2012	47.50	49.2	3.84	10	29	188	7.30	8.47
16-10-2012	59.79	62.4	4.85	10	28	54	7.58	4.08
23-10-2012	51.06	60.0	4.76	11	26	184	7.19	4.12
06-11-2012	69.11	71.9	5.84	6	17	62	7.40	2.86
13-11-2012	76.93	70.4	5.66	5	16	16	7.44	1.24
20-11-2012	63.59	58.8	4.70	6	17	77	7.30	3.24
26-11-2012	70.32	65.2	5.14	4	11	64	7.28	2.59
03-12-2012	66.18	73.8	5.88	6	17	160	7.56	1.46
10-12-2012	62.74	72.3	5.82	7	19	162	7.47	2.20
17-12-2012	63.00	62.1	4.86	8	25	49	7.21	3.53
25-12-2012	79.24	57.1	4.57	5	15	16	7.33	0.17
07-01-2013	58.86	52.4	4.05	11	31	13	7.20	4.86
14-01-2013	44.83	43.9	3.45	11	29	280	7.12	3.18
21-01-2013	47.27	42.2	3.22	6	15	420	7.34	4.06
29-01-2013	46.20	52.1	4.06	12	31	217	7.29	4.11
03-02-2013	41.09	35.4	2.79	12	28	234	7.12	6.73
12-02-2013	51.01	52.0	4.10	18	56	20	7.10	5.87
18-02-2013	49.23	36.7	2.94	12	31	69	6.98	6.38

(cont.)

WEEK	WQI	DO (%)	DO (mg/L)	BOD	COD	SS	pH	NH3N
25-02-2013	40.78	50.5	4.03	22	54	111	7.29	4.27
05-03-2013	39.08	45.9	3.57	18	42	242	7.07	6.29
12-03-2013	47.40	49.1	3.79	14	32	254	6.74	2.10
18-03-2013	44.00	60.4	4.66	17	41	262	7.18	7.07
25-03-2013	44.95	42.9	3.34	12	33	138	7.14	6.37
02-04-2013	45.74	50.8	3.85	10	34	267	7.12	6.30
08-04-2013	40.01	40.6	3.14	13	37	273	7.18	5.98
16-04-2013	44.98	52.7	3.90	18	39	115	7.15	5.53
23-04-2013	54.94	56.5	4.35	8	21	130	7.24	4.39
07-05-2013	64.61	71.5	5.59	6	33	59	7.00	4.04
14-05-2013	55.38	59.7	4.54	16	43	28	7.22	4.09
20-05-2013	46.96	51.3	3.96	17	48	108	7.01	2.52
28-05-2013	56.37	67.6	5.26	14	38	76	7.07	4.24
03-06-2013	51.31	46.8	3.57	15	44	32	6.98	5.08
10-06-2013	47.18	45.1	3.52	10	31	141	7.31	5.19
17-06-2013	45.64	39.1	2.97	17	49	51	7.27	7.33
25-06-2013	37.29	23.6	1.82	10	35	270	7.28	6.77
02-07-2013	48.78	57.4	4.42	11	37	171	6.84	5.03
10-07-2013	50.01	51.1	4.01	10	34	103	7.09	8.37
15-07-2013	40.06	48.1	3.75	27	31	163	7.11	9.27
23-07-2013	41.01	42.9	3.29	14	49	155	7.31	8.57
05-08-2013	46.42	36.7	2.88	16	59	23	7.14	12.36
13-08-2013	44.66	43.3	3.46	19	67	71	6.97	3.09
20-08-2013	55.22	58.9	4.73	14	27	81	6.80	4.81
26-08-2013	43.93	48.6	3.78	21	60	82	7.38	4.16
03-09-2013	58.80	67.8	5.40	11	32	82	6.86	6.46
09-09-2013	58.24	45.3	3.61	10	31	14	7.20	3.34
17-09-2013	59.76	66.4	5.31	11	33	57	6.98	4.33
24-09-2013	47.92	31.5	2.49	13	37	41	7.05	9.35
08-10-2013	44.63	27.4	2.14	18	52	12	6.97	9.62
13-10-2013	60.44	53.9	4.23	7	22	55	7.40	4.08
22-10-2013	50.21	55.5	4.29	21	59	24	7.24	7.06
28-10-2013	66.34	60.8	4.69	8	25	14	7.60	2.86
05-11-2013	62.35	54.9	4.40	8	26	16	6.75	4.28
12-11-2013	64.90	74.6	5.82	9	27	45	7.35	4.76
19-11-2013	55.38	56.6	4.47	12	39	51	7.31	4.00
26-11-2013	52.76	39.9	3.19	12	37	81	6.99	2.09
03-12-2013	67.08	56.4	4.64	10	34	21	6.71	0.99
09-12-2013	39.02	17.8	1.41	17	52	62	7.29	8.06
17-12-2013	37.54	7.5	0.59	17	53	56	6.82	5.88
24-12-2013	42.31	38.2	3.15	18	56	130	7.21	1.85

2. Station S7

WEEK	WQI	DO (%)	DO (mg/L)	BOD	COD	SS	pH	NH3N
11-05-2012	62.47	40.4	3.08	4	13	82	7.30	2.04
15-05-2012	65.08	46.5	3.66	4	11	27	6.89	3.48
21-05-2012	64.79	57.5	4.56	7	29	26	7.08	2.84
31-05-2012	56.61	45.5	3.54	9	35	34	6.86	3.39
08-06-2012	48.58	35.6	2.77	15	40	28	6.85	4.46
15-06-2012	74.46	31.5	2.52	3	15	25	6.87	0.02
20-06-2012	54.64	60.5	4.68	16	47	34	7.17	5.93
27-06-2012	54.33	40.7	3.24	9	33	35	7.03	4.83
03-07-2012	52.07	58.3	4.61	9	35	127	7.09	4.40
10-07-2012	50.82	58.5	5.48	19	68	35	6.87	3.63
17-07-2012	56.19	49.4	3.96	8	36	56	6.68	3.74
24-07-2012	75.19	68.9	5.51	2	6	17	7.08	3.74
03-08-2012	63.11	54.1	4.32	7	24	18	7.05	5.58
10-08-2012	54.18	42.9	3.38	12	32	23	7.04	6.60
16-08-2012	54.97	75.6	6.09	12	41	133	7.31	3.34
23-08-2012	68.87	75.0	5.96	8	24	23	7.26	3.47
04-09-2012	58.25	52.2	4.13	10	31	28	7.08	6.21
11-09-2012	59.77	44.9	3.52	7	21	26	7.40	6.37
18-09-2012	66.54	63.0	4.96	7	22	13	7.41	4.91
25-09-2012	68.52	74.0	5.84	7	21	41	7.16	3.52
02-10-2012	57.65	73.5	5.87	7	26	191	7.19	4.37
09-10-2012	56.00	62.5	4.88	12	35	84	7.15	6.30
16-10-2012	66.58	73.9	5.82	9	26	40	7.55	3.14
23-10-2012	60.41	78.4	6.26	9	36	111	7.29	2.74
06-11-2012	70.95	78.9	6.40	7	25	51	7.31	2.31
13-11-2012	71.81	83.6	6.76	5	16	107	7.52	1.13
20-11-2012	66.54	69.3	5.58	8	22	83	7.29	2.27
26-11-2012	71.94	76.9	6.04	7	19	57	7.31	1.97
03-12-2012	81.22	79.8	6.39	4	10	13	7.42	1.36
10-12-2012	71.23	72.4	5.84	6	19	71	7.26	1.77
17-12-2012	61.69	62.1	4.94	8	25	88	7.12	3.07
25-12-2012	71.21	71.9	5.82	6	18	10	7.30	3.69
07-01-2013	56.06	52.8	4.14	13	38	23	7.14	3.83
14-01-2013	59.68	61.9	4.94	12	34	27	7.13	4.37
21-01-2013	62.45	55.1	4.36	6	18	55	7.18	3.86
29-01-2013	66.21	95.8	7.72	11	35	61	7.36	3.19
03-02-2013	55.53	57.7	4.61	16	40	24	7.09	4.69
12-02-2013	66.16	61.2	4.86	6	13	43	7.13	4.19
18-02-2013	62.32	60.6	4.88	10	25	24	7.10	4.69

(cont.)

WEEK	WQI	DO (%)	DO (mg/L)	BOD	COD	SS	pH	NH3N
25-02-2013	64.42	67.7	5.47	9	25	38	7.19	3.72
05-03-2013	58.92	65.6	5.10	14	33	56	7.22	3.27
12-03-2013	63.34	69.4	5.47	10	22	107	7.15	1.48
18-03-2013	57.84	67.1	5.28	17	38	27	7.34	4.97
25-03-2013	56.44	71.0	5.59	11	31	125	6.74	3.25
02-04-2013	66.23	62.0	4.73	5	12	57	7.06	4.56
08-04-2013	65.17	55.9	4.35	6	14	32	7.02	4.62
16-04-2013	56.26	64.0	4.89	15	41	47	7.09	3.91
23-04-2013	58.61	64.8	5.01	10	28	88	7.59	4.16
07-05-2013	67.29	66.0	5.12	8	33	34	6.93	2.13
14-05-2013	62.84	66.6	5.10	13	36	18	7.09	2.99
20-05-2013	61.20	56.4	4.33	14	33	42	6.98	1.64
28-05-2013	56.48	64.1	4.94	16	44	31	7.62	3.64
03-06-2013	60.45	61.0	4.72	12	35	18	6.98	3.75
10-06-2013	66.27	65.6	5.24	8	22	21	7.37	3.79
17-06-2013	54.97	55.8	4.37	16	47	12	7.06	5.12
25-06-2013	55.78	64.0	5.00	15	53	48	7.21	3.19
02-07-2013	54.31	53.6	4.14	10	33	92	7.09	4.48
10-07-2013	58.63	49.0	3.85	8	29	32	7.13	7.68
15-07-2013	53.65	53.0	4.20	14	48	27	7.06	7.38
23-07-2013	55.03	53.3	4.16	12	43	34	7.14	6.88
05-08-2013	49.35	41.8	3.30	15	53	21	7.08	7.60
13-08-2013	57.08	64.2	5.10	12	45	50	7.12	4.42
20-08-2013	58.69	88.6	7.14	22	43	44	7.23	5.03
26-08-2013	58.76	62.5	4.94	13	39	24	7.23	4.41
03-09-2013	60.63	61.9	4.85	12	34	15	7.14	6.15
09-09-2013	64.06	67.5	5.41	11	32	23	7.34	3.10
17-09-2013	71.38	70.2	5.66	6	19	10	7.31	3.19
24-09-2013	61.65	45.7	3.64	7	20	8	7.11	7.32
08-10-2013	57.96	49.5	3.88	11	33	10	6.97	8.17
13-10-2013	65.46	70.4	5.56	10	30	25	7.41	3.19
22-10-2013	58.97	64.7	5.06	13	39	27	7.44	5.92
28-10-2013	62.86	69.1	5.36	14	43	16	7.50	2.55
05-11-2013	64.55	56.3	4.53	7	23	15	6.99	3.81
12-11-2013	67.79	91.6	7.20	9	29	41	7.52	4.21
19-11-2013	62.69	64.0	5.06	14	44	13	7.28	2.18
26-11-2013	63.20	53.1	4.17	6	18	32	7.29	4.23
03-12-2013	68.28	67.6	5.52	10	28	23	7.29	1.94
09-12-2013	58.15	48.2	3.89	9	28	26	7.32	5.18
17-12-2013	51.00	37.9	2.99	13	40	20	7.04	4.81
24-12-2013	45.28	34.1	2.74	16	50	43	7.20	3.81

3. Station S8

WEEK	WQI	DO (%)	DO (mg/L)	BOD	COD	SS	pH	NH3N
11-05-2012	67.10	52.9	4.02	4	13	63	7.25	2.22
15-05-2012	60.72	55.2	4.16	9	28	24	7.14	4.41
21-05-2012	65.10	56.1	4.48	5	26	36	7.12	2.93
31-05-2012	57.14	43.7	3.35	9	30	35	7.03	3.20
08-06-2012	43.63	26.1	2.04	16	33	70	7.02	4.05
15-06-2012	49.20	26.2	2.10	8	32	61	6.84	4.92
20-06-2012	56.20	46.9	3.63	9	30	43	7.14	4.01
27-06-2012	62.17	39.4	3.12	12	42	11	7.09	0.47
03-07-2012	59.63	50.6	3.97	6	29	47	7.11	4.16
10-07-2012	47.97	51.6	4.00	19	56	79	6.99	3.15
17-07-2012	56.07	31.8	2.54	6	28	17	6.66	4.07
24-07-2012	67.80	64.3	5.15	5	19	23	7.10	4.08
03-08-2012	58.49	46.1	3.67	9	32	8	7.03	4.64
10-08-2012	68.87	49.8	3.89	2	5	19	7.10	5.90
16-08-2012	59.30	75.3	6.08	9	34	233	7.17	1.77
23-08-2012	71.75	68.9	5.48	6	18	15	7.25	2.81
04-09-2012	52.09	35.5	2.81	10	32	36	7.08	6.37
11-09-2012	74.71	45.0	3.49	3	11	40	7.39	0.24
18-09-2012	62.70	58.5	4.57	7	23	41	7.41	4.09
25-09-2012	67.13	59.5	4.80	5	15	23	7.16	4.77
02-10-2012	64.00	67.9	5.40	8	31	35	7.18	5.08
09-10-2012	57.53	57.7	4.51	13	34	30	7.10	7.50
16-10-2012	67.65	71.0	5.63	9	27	22	7.54	2.86
23-10-2012	63.25	69.7	5.54	11	33	40	7.34	3.08
06-11-2012	74.36	75.6	6.14	5	14	50	7.26	2.00
13-11-2012	80.08	87.2	7.08	3	10	96	7.46	0.76
20-11-2012	66.57	64.7	5.21	7	22	91	7.25	1.93
26-11-2012	75.19	73.0	5.76	6	18	25	7.32	1.57
03-12-2012	74.08	77.0	6.16	6	17	97	7.40	0.88
10-12-2012	73.27	75.1	6.02	6	18	60	7.33	1.55
17-12-2012	67.46	60.4	4.80	6	15	52	7.14	2.65
25-12-2012	73.49	59.3	4.79	2	5	11	7.26	3.43
07-01-2013	56.70	72.8	5.69	15	52	54	7.16	4.59
14-01-2013	64.71	60.1	4.84	7	21	36	7.16	3.60
21-01-2013	60.93	59.6	4.76	9	27	42	7.16	4.38
29-01-2013	61.77	57.9	4.64	9	25	47	7.20	3.18
03-02-2013	57.22	54.5	4.35	14	36	12	7.10	3.90
12-02-2013	62.19	63.7	5.08	13	29	17	7.12	3.44
18-02-2013	59.02	53.2	4.26	10	21	46	7.09	4.13

(cont.)

WEEK	WQI	DO (%)	DO (mg/L)	BOD	COD	SS	pH	NH3N
25-02-2013	66.21	63.8	5.14	7	16	52	7.22	3.20
05-03-2013	56.03	54.4	4.20	13	31	41	7.18	4.63
12-03-2013	55.19	51.6	4.10	20	45	49	7.22	1.33
18-03-2013	54.05	59.6	4.68	17	40	45	7.20	4.01
25-03-2013	67.49	76.7	5.98	11	32	41	6.84	2.23
02-04-2013	71.24	90.5	6.89	8	19	27	7.11	4.45
08-04-2013	62.24	57.7	4.45	9	26	19	7.13	4.29
16-04-2013	60.99	62.8	4.74	11	31	26	7.19	4.00
23-04-2013	61.61	62.3	4.79	11	33	51	7.24	2.58
07-05-2013	65.35	62.3	4.78	10	39	18	6.92	2.09
14-05-2013	55.84	56.2	4.33	18	45	12	7.05	3.18
20-05-2013	63.32	63.5	4.91	14	41	30	6.96	1.55
28-05-2013	60.85	66.7	5.13	17	47	16	7.67	2.22
03-06-2013	66.16	59.1	4.58	9	26	8	6.99	2.79
10-06-2013	68.51	81.8	6.44	11	32	14	7.38	3.05
17-06-2013	57.19	47.0	3.98	11	33	8	7.14	4.27
25-06-2013	51.50	40.4	3.21	14	48	40	7.32	2.47
02-07-2013	58.61	48.0	3.65	8	29	27	7.22	4.30
10-07-2013	54.25	48.7	3.83	11	38	42	7.24	7.57
15-07-2013	61.33	54.1	4.28	8	30	18	7.06	7.23
23-07-2013	61.32	55.9	4.40	9	32	13	7.00	6.22
05-08-2013	43.04	37.2	2.94	22	77	15	7.01	7.61
13-08-2013	57.93	55.2	4.38	10	36	35	6.90	4.51
20-08-2013	57.35	83.1	6.71	21	51	41	7.15	5.11
26-08-2013	60.72	75.5	5.97	16	48	18	7.33	3.54
03-09-2013	68.41	69.6	5.55	8	24	10	7.25	3.60
09-09-2013	62.67	63.6	5.07	11	33	24	7.31	3.14
17-09-2013	54.83	48.7	3.95	13	39	18	7.35	3.84
24-09-2013	58.80	50.7	4.04	10	29	20	6.97	6.92
08-10-2013	61.58	56.9	4.46	10	29	11	6.88	7.06
13-10-2013	65.04	65.2	5.17	8	24	38	7.46	3.36
22-10-2013	61.11	67.8	5.26	12	36	25	7.41	5.88
28-10-2013	62.90	77.7	6.05	18	55	12	7.58	2.18
05-11-2013	61.70	59.8	4.82	10	32	16	6.84	3.86
12-11-2013	75.84	88.8	7.05	6	19	12	7.47	2.84
19-11-2013	57.75	53.5	4.27	12	37	14	7.30	3.80
26-11-2013	55.96	52.5	4.12	16	49	17	7.25	2.58
03-12-2013	65.63	53.4	4.39	9	28	14	7.37	1.88
09-12-2013	54.70	48.7	3.98	12	38	27	7.27	5.58
17-12-2013	55.32	28.5	2.25	8	25	17	7.03	3.36
24-12-2013	47.08	41.7	3.36	16	50	51	7.19	3.85

4. Station S25

WEEK	WQI	DO (%)	DO (mg/L)	BOD	COD	SS	pH	NH3N
11-05-2012	78.12	71.3	5.50	3	8	32	7.13	1.70
15-05-2012	63.00	45.7	3.59	6	22	22	6.84	2.98
21-05-2012	73.89	61.4	4.86	6	27	41	7.15	0.40
31-05-2012	65.73	46.0	3.45	4	16	86	6.93	1.21
08-06-2012	47.20	31.5	2.48	15	40	30	6.83	4.43
15-06-2012	68.07	18.6	1.48	5	22	33	6.87	0.01
20-06-2012	55.48	46.3	3.56	11	35	21	7.26	6.92
27-06-2012	54.69	41.0	3.26	12	32	10	7.03	7.19
03-07-2012	62.32	38.6	3.01	6	26	46	6.95	1.38
10-07-2012	64.65	42.9	3.24	6	27	35	7.10	1.25
17-07-2012	57.06	37.2	2.99	5	18	52	6.69	4.00
24-07-2012	68.11	54.5	4.28	3	12	19	7.13	4.03
03-08-2012	45.09	22.9	1.85	15	48	15	6.79	7.51
10-08-2012	53.46	32.6	2.60	10	28	17	7.00	6.61
16-08-2012	67.02	57.4	4.64	3	8	79	7.08	3.28
23-08-2012	57.39	44.7	3.55	8	25	44	7.11	3.73
04-09-2012	54.37	41.7	3.29	10	32	31	7.17	6.32
11-09-2012	56.73	36.2	2.82	7	20	28	7.40	6.82
18-09-2012	74.86	54.9	4.32	5	19	36	7.40	0.24
25-09-2012	70.55	66.3	5.26	5	13	24	7.26	3.36
02-10-2012	62.65	83.3	6.73	6	20	196	7.25	3.20
09-10-2012	62.91	79.4	5.96	12	33	45	7.54	4.08
16-10-2012	74.59	76.8	6.09	5	12	16	7.55	3.06
23-10-2012	69.32	75.1	6.06	6	17	75	7.36	2.81
06-11-2012	74.55	72.3	5.86	5	16	27	7.33	2.06
13-11-2012	82.99	81.1	6.60	4	13	7	7.50	0.89
20-11-2012	67.05	69.5	5.60	9	28	51	7.28	2.15
26-11-2012	71.24	57.2	4.41	6	18	6	7.23	2.01
03-12-2012	79.97	79.5	6.42	6	17	32	7.50	1.03
10-12-2012	72.51	67.7	5.46	5	15	58	7.23	1.55
17-12-2012	75.35	90.5	7.18	5	15	49	7.18	2.56
25-12-2012	63.07	42.7	3.40	6	16	10	7.27	3.38
07-01-2013	53.02	50.0	3.93	13	40	47	7.17	3.84
14-01-2013	58.00	52.1	4.15	10	29	35	7.10	4.54
21-01-2013	60.07	57.9	4.57	9	26	49	7.17	4.75
29-01-2013	55.25	47.4	3.77	11	31	51	7.40	3.32
03-02-2013	56.87	52.1	4.14	14	35	11	7.07	3.79
12-02-2013	78.54	76.1	5.90	5	12	28	7.12	1.22
18-02-2013	63.45	56.1	4.42	8	20	27	7.09	3.50

(cont.)

WEEK	WQI	DO (%)	DO (mg/L)	BOD	COD	SS	pH	NH3N
25-02-2013	58.73	66.3	5.27	15	42	36	7.07	3.25
05-03-2013	65.96	52.1	4.20	16	46	40	7.48	0.03
12-03-2013	68.72	63.8	4.68	8	16	70	7.19	1.43
18-03-2013	55.11	54.0	4.25	15	34	32	7.19	5.15
25-03-2013	57.61	46.1	3.53	9	24	81	7.08	2.56
02-04-2013	67.85	65.2	4.97	5	13	43	7.06	4.52
08-04-2013	57.08	49.9	3.89	10	29	39	7.05	4.22
16-04-2013	63.78	62.0	4.76	8	24	33	7.02	3.93
23-04-2013	52.76	60.4	4.69	15	43	75	7.41	4.19
07-05-2013	63.92	60.2	4.70	9	29	39	6.91	2.53
14-05-2013	65.13	67.4	5.20	11	32	14	7.10	3.02
20-05-2013	63.23	66.8	5.19	12	36	59	7.14	1.94
28-05-2013	63.68	66.7	5.20	10	29	20	7.65	3.78
03-06-2013	59.95	51.1	4.00	10	30	10	6.97	3.77
10-06-2013	57.10	52.3	4.17	13	36	19	7.28	3.49
17-06-2013	48.60	43.1	3.37	19	56	10	7.09	4.94
25-06-2013	74.36	98.1	7.42	8	29	24	8.28	1.64
02-07-2013	61.42	67.6	5.29	10	37	36	7.34	4.15
10-07-2013	58.17	43.8	3.42	8	28	54	7.56	2.49
15-07-2013	58.65	51.5	4.11	9	31	28	7.09	7.14
23-07-2013	51.44	48.3	3.76	14	47	36	7.25	7.09
05-08-2013	50.35	37.1	2.93	13	46	14	7.27	7.75
13-08-2013	63.18	59.8	4.81	7	28	45	7.21	3.37
20-08-2013	57.91	54.8	4.44	14	21	36	6.85	4.55
26-08-2013	79.82	38.9	3.09	2	5	19	7.27	0.03
03-09-2013	70.74	100.6	8.04	9	27	18	7.14	5.94
09-09-2013	60.75	62.5	5.04	14	41	18	7.36	2.70
17-09-2013	69.56	68.7	5.52	7	28	7	7.07	3.05
24-09-2013	56.60	32.2	2.58	8	23	6	7.11	7.04
08-10-2013	52.90	32.7	2.58	11	32	9	6.99	7.53
13-10-2013	66.47	62.5	4.97	7	21	24	7.45	3.45
22-10-2013	59.29	63.8	4.96	14	42	9	7.40	5.17
28-10-2013	65.51	61.1	4.80	9	28	12	7.48	2.85
05-11-2013	60.74	66.7	5.29	13	40	13	7.26	4.31
12-11-2013	67.38	78.4	6.18	8	27	31	7.60	4.28
19-11-2013	55.91	56.3	4.50	15	46	14	7.46	3.64
26-11-2013	53.01	42.4	3.37	13	41	27	7.24	3.17
03-12-2013	57.01	46.6	3.82	9	44	26	7.27	2.87
09-12-2013	52.89	38.8	3.13	12	38	11	7.23	5.18
17-12-2013	45.89	11.8	0.94	12	36	20	6.77	4.71
24-12-2013	41.99	29.4	2.40	17	51	94	7.31	2.94